Chapter 30
Measurement of Customer Equity from the Perspective of Data Mining

Pengfei Wang and Manyu Huang

Abstract As the uncertainty of individual customer's consumption behavior makes it difficult to measure customer equity, the present paper advances a dynamic method for the measurement of Customer Equity on the basis of a data-mining technique and the classification of customers. It starts by introducing the process and method for calculation, and subsequently it demonstrates the application of the method by empirical analysis. The method enables the measurement of Customer Equity in a more accurate and practical way, and hence it may offer significant support for enterprises to achieve more effective marketing.

Keywords Customer equity · Data mining · Customer lifetime value

30.1 Introduction

Nowadays, an increasing number of enterprises are turning from a product-centric to a customer-centric approach when they establish the marketing strategies under pressure from fierce competition. Practice has proved that the customer-centric competition strategy may help enterprises gain sustainable competitive advantages. The concept of Customer Equity appears when enterprises regard customers as equity under the guidance of customer-centric idea. In addition, the concept of Customer Lifetime Value has been advanced by many Western scholars. For example, Reichheld [1] defines Customer Lifetime Value as the present value of

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the expected benefits (e.g., gross margin) less the burdens (e.g., direct costs of servicing and communicating) from each customer. Consequently, Customer Equity is the sum of all Customer Lifetime Value. The measurement of customer helps to quantify the relationship between enterprises and customers so as to offer useful tools for marketing decisions.

Current measurement of customer equity is mainly implemented by summing up Customer Lifetime Value. For example Berger [2] advances a mathematics equation for the calculation of Customer Lifetime Value under two kinds of contexts: maintenance and migration of customers. However, it only applies to current customers and only demonstrates static characteristics of Customer Equity. Phillip [3] puts forward a customer relationship model on the basis of Markov Chain, but it still lacks quantified and dynamic analysis for taking both the maintenance of current customers and exploration of potential customers into consideration.

The measurement of Customer Equity focuses on a more accurate prediction of customers' future consumption [4]. However, it is difficult to estimate the customers' future consumption from the past consumption data, as the uncertainty for the individual customer's future consumption behavior is significant. In addition, potential customers should not be excluded and the dynamic characteristic should be taken into consideration when Customer Equity is calculated. Consequently, the classification of customers is helpful to overcome the above-mentioned disadvantages, as the customers who belong to the same category display more stable consumption behavior [5]. Hence the present paper aims to classify customers according to expenditure and gross profit on the basis of data-mining technique. It will then move on to a consideration of rules of customers' expenditure modes by using data-mining techniques for each category. Moreover, demographic variables (such as sex, age, occupation, and income) and consumption behavior variable (such as regency and consequence of consumption, money spent and changing rate of money spent) will be considered when data-mining technique is applied to determine inner and outer factors that influence the changing of expenditure modes for each category. Finally, as Customer Equity is predicted more precisely, higher quality data for marketing references may be offered.

30.2 Measurement Methods

30.2.1 Research Framework

The calculation of Customer Equity is achieved by summing up Customer Lifetime Value, while the conceptual framework for the calculation of Customer Lifetime Value can be illustrated as follows:

Among all the factors shown in Fig. 30.1 that influence Customer Lifetime Value, sales and the predicted period (i.e., customers' maintenance period) are

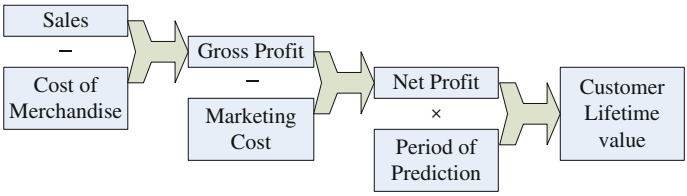

Fig. 30.1 The conceptual frame of the calculation of customer lifetime value

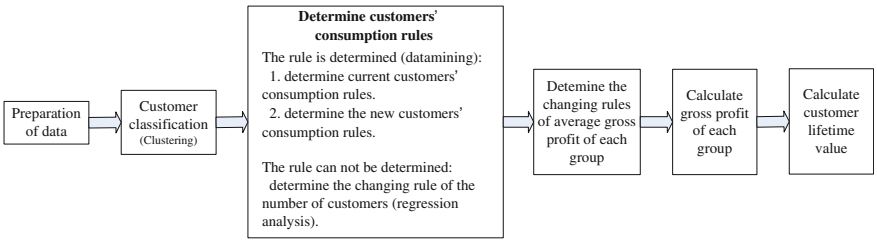

Fig. 30.2 Calculation process of customer equity

decided by customers, making thus the prediction of these variables crucial to the measurement of Customer Lifetime Value As the consumption behavior of the individual customer is to a great extent uncertain, the prediction of sales and the maintenance period will be inaccurate if the measurement is done from the perspective of the individual customer. In addition, this type of measurement only focuses on current customers and potential customers are ignored.

Thus, the present paper aims to determine consumption rules on the basis of customer groups which tend to have similar consumption behavior, so as to obtain more reliable results in terms of measurement. The Customer Lifecycle Theory explains that there should be a certain rule of consumption model during the maintenance of customers, and the determination of this rule may help to predict sales and the maintenance period, so that a more accurate prediction can be made.

In my proposed method, the calculation of Customer Equity is achieved not by summing up individual Customer Lifetime Value, but by seeking for consumption rules on the basis of customer classification. The process can be illustrated as follows (Fig. 30.2).

There are two situations to consider when Customer Equity is measured: one is when the consumption rules exist and the other one is when the rules do not exist. Hence, the present paper focuses only on the situation when the rules can be tracked.

30.2.2 Customer Classification on the Basis of Clustering Analysis

Accurate prediction of customers' future consumption is crucial for the calculation of Customer Equity. Yet, the great uncertainty of individual customer's consumption means that it is difficult to predict one's future consumption behavior only according to past consumption. In addition, the potential customers should not be excluded when Customer Equity is calculated, and the dynamic characteristics should be manifested. As the consumption rules of customer groups should be more stable and dynamic, so the classification of customers should be the precondition of the calculation of Customer Equity. Therefore, this paper will classify customers according to their expenditure and the gross profit which customers create for the enterprise by using the clustering method.

Here the paper uses K-means clustering to classify customers. N stands for the number of customers, $S1$, $S2$ … SN is their expenditures separately, P_1, P_2 … P_N refer to the gross profit accordingly, so that (S_i, P_i) means customer i's expenditure and gross profit $(1 \leq i \leq N)$. Consequently, the distance (refers to the similarity) between customer i and j is as follows:

$$d_{ij} = \sqrt{\alpha(S_i - S_j)^2 - (P_i - P_j)^2} \tag{30.1}$$

α is weight, and $\alpha = \left(\sum P / \sum S\right)^2$

Here the k-medoid method is used for classification. The number of categories should be decided at first, supposing it K. The classification can be finished by using the data-mining technique, and the result will be more reasonable than those obtained by manual estimation.

30.2.3 Calculation of Customer Equity

30.2.3.1 Determination of Customers' Consumption Rules

The customers of an enterprise can be classified into different categories according to their consumption rules, and data-mining technology can be productively used for the determination of these rules.

Let us suppose that an enterprise has N customers, and the number of groups is K; Ri stands for the expenditure of customer i, and $Ri = \{C1, C2\ldots, Ct\}$, where Cj refers to the group customer i belongs to in period j, $0 \leq Cj \leq K$ ($j = 1, 2\ldots, t$). $Cj = 0$ means the churn of customer j, and t stands for the life period of customer j. M stands for the number of customers who have the same expenditure rule as Ri, if $M/N \geq P0$, and $L = \{C1, C2\ldots, Ct\}$ can be defined as a piece of consumption rule.

First, the consumption record Ri ($i = 1, 2, \ldots, N$) of all the customers is scanned, second, those customers who have the same consumption record are registered to see if the registered amount exceed the stipulated amount, those exceeding ones are initial consumption rules. Third, the initial consumption rules are scanned and compared, and those sub-rules (rules contains in other consumption rules) are filtrated, and the rest is used as final consumption rules for output. The detailed arithmetic is as follows:

$i = 1, j = 1, TLj = Ri, Mj = 1$; B: $i = i + 1$; for $k = 1$ to j if $Ri = Lk$ then $Mk = Mk + 1$; else $j = j + 1$, $TLj = Ri$, $Mj = 1$; next k if $i < N$ then goto B; $m = 0$; for $k = 1$ to j if $Mk/N \geq P0$ then, $m = m + 1, Lm = TLk$; next $kn = 0$; for $i = 1$ to m for $j = 1$ to m if $Li \in Lj$ then next I; else, $n = n + 1$, $Ln = Li$; next j next i output Lj, $1 \leq j \leq n$. Finally, n pieces of consumption rules can be obtained and they are saved in $L1$, $L2 \ldots$, Ln separately.

30.2.3.2 Definition Current Customers' Consumption Rules

Each piece of consumption rules predicts the future consumption behavior of customers who belong to the rule, and the future expenditure and gross profit of each period can thus be predicted. The present paper adopts the Decision Tree method in order to judge to which consumption rule each customer belongs. Not only the expenditure record but also some demographic variables (sex, age, occupation, income, among others.) and consumption behavior variables (regency, frequency, expenditure, and the changing rate of expenditure) are all taken into consideration as distinguishing attributes, while the current consumption rules of customers are used as class attribute. As a consequence, the decision tree for distinguish customers consumption behavior can be obtained in this way.

Discriminate classification calculation is implemented by using the decision tree so as to decide current customers' consumption rule and the consumption period they belong to. In addition, this calculation can also be adapted to new customers.

30.2.3.3 Determination of the New Customer's Consumption Rule

After obtaining the consumption rules of current customers, the consumption rules of new customers must be determined. The new customers for each group originate from two sources: one is from the enterprises other groups; the other is totally new for the enterprise. Concerning the former, the consumption rule has been decided before the migration, so only the rules for the latter need to be determined. Accordingly, here the new customers refer to the new added customers. The rules of new added customers include the number of new customers and the percentage of new added customers adopts a certain kind of consumption rule.

The number of new customers can be estimated by time serial analysis according to the number of old customers of each group and the marketing cost for

each group. The percentage of the adoption of a certain consumption rule by new customers can be calculated on the basis of the average percentage of the adoption of a certain consumption behavior by new customers in each period.

30.2.3.4 Determination of the Changing Rules of Gross Profit for Each Customer Group

The performance and quality of product, price, income, etc., are all factors that influence the gross profit. However, it is unnecessary to research the changing rules of gross profit of the individual customer since all the customers are classified, and it may be helpful to estimate the changing rules of average gross profit of each customer group with similar consumption characteristics. The past average gross profit of a customer group relates to the current gross profit, as most customers are inclined to maintain their consumption characteristics. In addition, marketing expenses influence the gross profit of customers greatly, for instance, the price reduction of a certain product In this case, the reduction can be regarded as marketing expenses, and so to be taken as the main factor that influences customers' average gross profit.

The ARMA model of time serial analysis is used to build the changing model of gross profit of each customer group, where the independent variable is the average profit of customers from the last period and the marketing expenses in the current period. First, the average gross profit of each group in the period needs to be calculated. Here, $X_1, X_2 \ldots, X_N$ refers to the number of customers in period 1, 2, …, n. $S_1, S_2 \ldots SX_i$ is the gross profit of X_i in the year of i, Y_i is the average gross profit in year I, so $Y_i = \frac{1}{X_N}\sum_{m=1}^{X_N} S_m$, $1 \le i \le N$. Consequently, the average gross profit of the customer group in each period $Y_1, Y_2 \ldots, Y_N$ can be acquired.

Supposing that the marketing fee for the group in period N is $Z_1, Z_2 \ldots, Z_N$ and the ARMA model of time serial analysis for average gross profit of the group can be built as:

$$Y_t = b_0 + b_1 Y_{t-1} + b_2 Z_t \tag{30.20}$$

b_0, b_1, b_2 all the coefficients can be obtained by calculating, so the ARMA model for the prediction of gross profit of the group for next period can be thus determined. For instance, the average gross profit in period of $N + 1$ $YN + 1$ can be predicted by including YN and $ZN + 1$ (here $ZN + 1$ is the planned marketing fee for period $N + 1$) into the model.

30.2.3.5 Measurement of Customer Equity

The expenditure of each customer and the marketing cost of each period is now recorded. The span of the period is decided according to the enterprises' sales and the demand of application, so it can be a year, a few months, or a few weeks. For

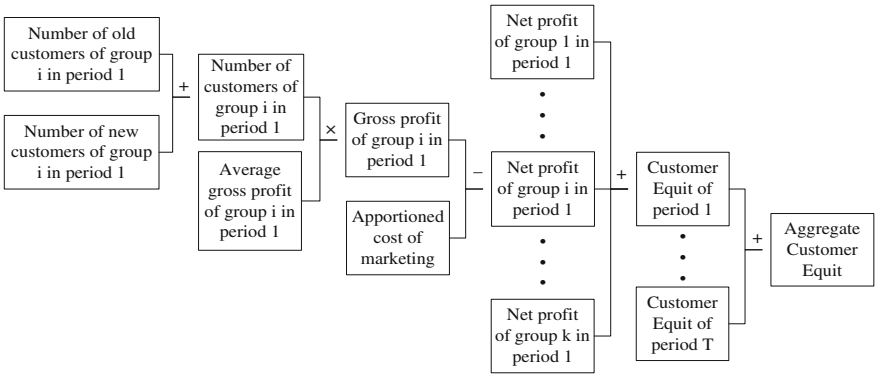

Fig. 30.3 Calculation method of customer equity when the consumption rule can be determined

the sake of the simplification of analysis, the present paper assumes that each period is a year, and the number of groups is *K*. *I* will then move on to predict Customer Equity from period 1 to *T*.

The aggregate Customer Equity is the summing up of Customer Equity in period 1 to *T*, and Customer Equity in each period is the summing up of the net profit from *K* groups. The profit of each group in each period, for instance, the net profit of group *i* in period 1, can be calculated as follows:

The number of old customers of group *i* in period 1 + the number of new customers of group *i* in period 1 = the number of customers of group *i* in period 1

The number of customers of group *i* in period 1 * the average gross profit in group *i* in period 1 = gross profit of group *i* in period 1

The gross profit of group *i* in period 1 − the apportioned cost of marketing = the gross profit of group *i* in period 1

Here, the number of old customers and new customers of group i in period 1 is determined by the rules mentioned in Sects. 30.2 and 30.3, and the average gross profit of group *i* in period 1 is calculated by Eq. (30.1). The calculation method of aggregate Customer Equity is illustrated in the following Fig. 30.3.

30.3 Conclusion

Customer Equity is a pioneering concept and its calculation is determined on the basis of customer database with the application of data-mining technology and statistical methods. Customer Lifetime Value and Customer Equity are currently an important reference for marketing decisions and the allocation of marketing resources in many foreign companies. Thus, the present study focused on this development tendency, and it researched a dynamic method for the calculation of Customer Equity by using data mining technology. In addition, the application of

the calculation of Customer Equity in the marketing decision of companies was implemented through empirical analysis. The conclusions reached are as follows.

First, the application of data-mining technology to the measurement of Customer Equity makes the calculation more precise and applicable. Although the measurement and application of Customer Equity have aroused great interest in many scholars, there are still many limitations in this respect. For instance, there are large gaps between the application and the theoretical assumptions of many models; most of the research conducted does not take the dynamic trait of Customer Equity into consideration. The present paper applies data-mining technology to the calculation on the basis of the theoretical models of Customer Equity.

The paper advances the calculation of Customer Equity on the basis of the classification of customers. As the great uncertainty of individual customer makes it rather difficult to predict the consumption behavior, calculation by classification of customers solves the problem successfully by making the calculation more accurate.

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